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CONDITION MONITORING OF AIR COMPRESSOR IN STEEL INDUSTRY USING *ANFIS*

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ABSTRACT

As large rotating machines are increasingly employed in continuous operations at high speeds and with heavy loads, vibration behavior of rotating systems is emerging as more complex phenomenon. Monitoring vibration behaviour of large rotating machinery is an effective way to reduce losses and enhance safety, reliability, availability and durability in manufacturing processes. This research focuses on condition monitoring of one of the vital and the most critical machine Air Compressor of steel industry. It considers vibration levels of the machinery based on ISO limit of vibration severity using Adoptive neuro fuzzy inference system (ANFIS). Two different data schemes were formulated based on preliminary experimentation on Sugeno type 3 inputs (v_{Hm}, v_{Vm} & v_{Am}) and 1 output (i. e., Condition) ANFIS model. The performance criterion of the ANFIS classifier was evaluated using confusion matrix. The total classification accuracy of 95% obtained proves the validation of the Air Compressor model. ANFIS can also be extended to condition monitoring of various rotating machinery.

KEYWORDS: Air Compressor, Condition Monitoring, ANFIS, Vibration Severity & Sugeno Method

Original Article

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1. INTRODUCTION

The main aim of vibration monitoring is to maximize, availability, reliability and efficiency of a plant from the installed machines, aiming at excellent results. It is necessary to avoid the break downs, which may lead to production loss in industry and huge repair and maintenance cost. The effects of vibration are unbalanced forces in a machine and improper alignment, aero dynamic forces etc. Vibration monitoring is being extensively used in industries for online condition monitoring (*CM*) of rotating machineries. The current status of rotating machinery can be monitored based on *ISO* vibration severity limits [1]. If the vibration levels exceed the said *ISO* limits, imminent major defects may lead to catastrophic failure of machinery. Hence, diagnosis has to be carried out from the operational safety point of view. In condition monitoring, there are several indicating phenomenon like vibration, noise, heat, debris in oil and sound beyond human abilities etc., which emanate from these inefficiently running machines [2].

There are many systems available today, that provide online or continuous monitoring of rotating machinery for condition based maintenance in production plants. This research presents condition monitoring of Air compressor, which is one of the critical machinery in production of steel using *ANFIS*.

2. LITERATURE SURVEY

Maintaining high levels of availability and reliability is an essential objective for all production units, especially for those that are subject to high costs due to loss of production [3]. Many signal analysis methods are able to extract useful information from vibration data. Currently, most of these methods use spectral analysis based on Fourier Transform (*FT*) [4]. Investigation of effect of vibrations at the bearings due to simulated faults like parallel misalignments, angular misalignment, combined parallel and angular misalignments and unbalances was done on a rotor rig. Vibration accelerations in vertical, horizontal and axial directions have been monitored using a piezoelectric accelerometer [5]. Investigation of spike energy and frequency spectrum leads to identification of problem with races of roller bearings [6]. Modal Testing is a technique used to obtain the modal and dynamic response properties of structures. The raw data obtained from experiment was simulated on finite element (*FE*) model using *ANSYS 12*. Together with eigen analysis and graphical facility good result were obtained [7]

Artificial neural network (*ANN*) and wavelet transform (*WT*) were applied to vibration signature, for the prediction of effect of the combined faults of unbalance and shaft crack of rotating machinery. A new technique combining *ANN* with three general tasks- data acquisition, feature extraction, and fault identification was considered [8]. An adaptive neural network is a network structure consisting of a number of nodes connected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. Learning or training phase of a neural network is a process to determine parameter values to sufficiently fit the training data. *ANFIS* is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [9].

A Sugeno type Adaptive Neuro Fuzzy Inference System with three input nodes Horizontal (v_H), Vertical (v_V) and Axial (v_A) velocities and one output node was used. The input consists of the velocity vector obtained by extraction of amplitudes for the characteristic velocities of the machinery used in our experimental setup, with the fault state as the output [10].

Three inputs in their vector order are v_H, v_V and v_A rms velocity amplitudes. 300 data sets were collected for training. Out of these 300, 20 data sets were randomly selected for testing. A separate set of 24 data sets were collected for checking and characterization of faults. Thus, total of 324 data sets were considered for the purpose of analysis. The network first fuzzifies each input with two membership functions that can be classified as low and high depending on the value of the velocity amplitudes. The input membership functions v_{Hl}, v_{Hh} v_{Vl}, $v_{Vh,}$ v_{Al} and v_{Ah} velocities and their types (i. e., Gaussian) are then combined to form the rule base [11]. There are three criteria to determine the test performance of classifier. These criteria are Sensitivity (*ST*), Specificity (*SP*) and Total Classification Accuracy (*TCA*) [12].

3. EXPERIMENTATION

Air compressor is selected as a critical machine driven by a motor running at speed of 2975 rpm. It is connected to the air compressor by a flexible coupling. The shaft is supported on bearings is shown in Figure 1. The bearing pedestals and vibration pads are provided in order to fix a tri-axial accelerometer. The dynamic vibration levels in horizontal, vertical and axial directions are measured. The frequency analysis is carried out using a Fast Fourier Transform (*FFT*) analyzer. The tri-axial accelerometer enables measurements of the vibration level in the horizontal, vertical and axial directions. The output of the tri-axial accelerometer was connected to a multiplexer. The output of a Multiplexer was connected to a *FFT* analyzer as shown in Figure 2. *FFT* analyzer was in turn interfaced to a computer.

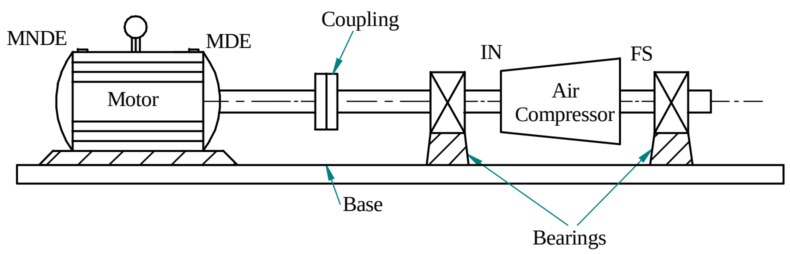


Figure 1: Schematic of Air Compressor Set up and Accelerometer Location

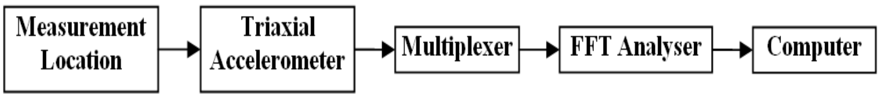


Figure 2: Instrumentation for Vibration Analysis of Air Compressor

4. FAULT CONDITIONS

Two measurement locations were considered for determining the vibration severity. One location each on driver (*MNDE*) and driven end (*MDE*) of motor were chosen for accurate identification of faults, in addition to First Stage (*FS*) of Compressor. It is necessary to define normal and faulty operating conditions of the machinery in a digital form for computational purpose. This is done by representing the state of a particular type of fault, with a specific membership classification. Fault states are decided on the basis *ISO* limit of vibration severity criterion of the mill stand which is suggested as 4.5 mm/s. Magnitudes of velocity components along horizontal, vertical and axial directions were considered for the purpose. If the *RMS* values are ≤ 4.5 mm/s, the condition is normal and the fault state *0*, was assigned and if the values are > 4.5 mm/s, the condition is abnormal and the fault state *1*, was assigned. Velocities measured at different locations by using *FFT* and tri-axial accelerometer recorded in Tables 1 to 3. The corresponding plots are as shown in Figures 3 to 5.

Figure 3 gives the vibration behaviour at *MNDE.*

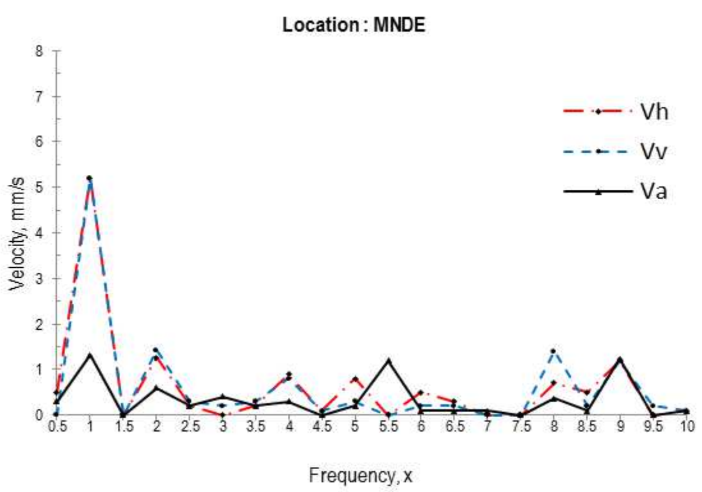


Figure 3: Rotor behaviour at *MNDE*

Table 1: *FFT* Analysis at *MNDE*

Sl. No	Freq, *f*		Velocity (mm/s)		
	x	rpm	v_H	v_V	v_A
1	0.5	1500	0.50	0.00	0.30
2	1.0	3000	5.20	5.20	1.32
3	1.5	4500	0.00	0.00	0.00
4	2.0	6000	1.26	1.42	0.60
5	2.5	7500	0.20	0.30	0.20
6	3.0	9000	0.00	0.20	0.40
7	3.5	10500	0.20	0.30	0.20
8	4.0	12000	0.90	0.80	0.30
9	4.5	13500	0.10	0.10	0.00
10	5.0	15000	0.80	0.30	0.20
11	5.5	16500	0.00	0.00	1.20
12	6.0	18000	0.50	0.20	0.10
13	6.5	19500	0.30	0.20	0.10
14	7.0	21000	0.00	0.00	0.10
15	7.5	22500	0.00	0.00	0.00
16	8.0	24000	0.70	1.40	0.36
17	8.5	25500	0.50	0.20	0.10
18	9.0	27000	1.20	1.20	1.24
19	9.5	28500	0.00	0.20	0.00
20	10.0	30000	0.10	0.10	0.10

The successive predominant velocities, *1x* velocities v_H (= 5.2 mm/s) and v_V (= 5.2mm/s) are radial, hence the machine has Force Unbalance or Mechanical Looseness-A.

Figure 4 gives the vibration behaviour at *MDE*.

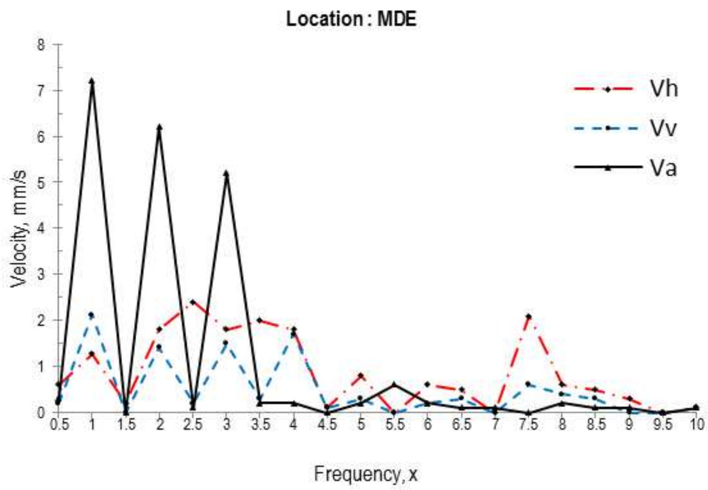


Figure 4: Rotor Behaviour at *MDE*

Table 2: *FFT* Analysis at *MDE*

Sl. No	Freq, *f*		Velocity (mm/s)		
	x	rpm	v_H	v_V	v_A
1	0.5	1500	0.60	0.20	0.30
2	1.0	3000	1.28	2.13	7.20
3	1.5	4500	0.20	0.00	0.00
4	2.0	6000	1.80	1.42	6.20
5	2.5	7500	2.40	0.20	0.10
6	3.0	9000	1.80	1.50	5.20
7	3.5	10500	2.00	0.30	0.20
8	4.0	12000	1.80	1.70	0.20
9	4.5	13500	0.10	0.10	0.00
10	5.0	15000	0.80	0.30	0.20
11	5.5	16500	0.00	0.00	0.60
12	6.0	18000	0.60	0.20	0.20
13	6.5	19500	0.50	0.30	0.10
14	7.0	21000	0.00	0.00	0.10
15	7.5	22500	2.10	0.60	0.00
16	8.0	24000	0.60	0.40	0.20
17	8.5	25500	0.50	0.30	0.10
18	9.0	27000	0.30	0.00	0.10
19	9.5	28500	0.00	0.00	0.00
20	10.0	30000	0.10	0.10	0.10

Velocity amplitudes predominant in succession, *1x* (v_A=7.2 mm/s), *2x* (v_A= 6.2 mm/s), and *3x* (v_A=5.2 mm/s), all in axial direction. It indicates Angular Misalignment in the machinery.

Figure 5 gives rotor behavior at *FS.*

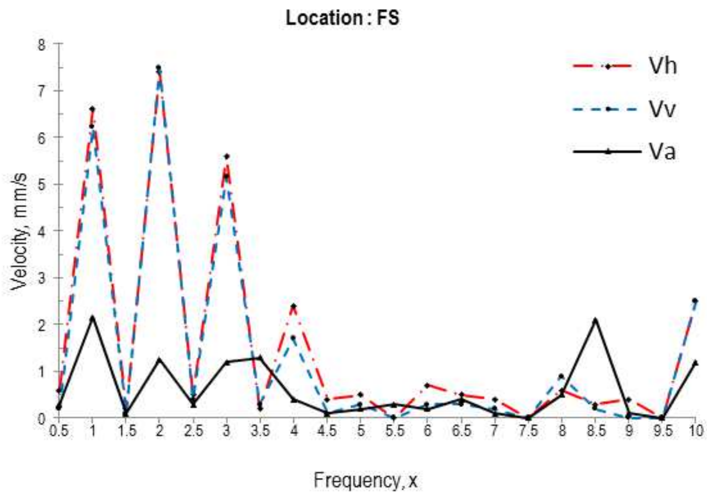


Figure 5: Rotor behaviour at *FS*

Table 3: *FFT* Analysis at *FS*

Sl. No	Freq, f		Velocity (mm/s)		
	x	rpm	v_H	v_V	v_A
1	0.5	1500	0.60	0.20	0.30
2	1.0	3000	6.62	6.23	2.15
3	1.5	4500	0.20	0.10	0.10
4	2.0	6000	7.40	7.49	1.25
5	2.5	7500	0.50	0.40	0.30
6	3.0	9000	5.60	5.15	1.20
7	3.5	10500	0.20	0.30	1.30
8	4.0	12000	2.40	1.70	0.40
9	4.5	13500	0.40	0.10	0.10
10	5.0	15000	0.50	0.30	0.20
11	5.5	16500	0.00	0.00	0.30
12	6.0	18000	0.70	0.30	0.20
13	6.5	19500	0.50	0.30	0.40
14	7.0	21000	0.40	0.20	0.10
15	7.5	22500	0.00	0.00	0.00
16	8.0	24000	0.60	0.90	0.50
17	8.5	25500	0.30	0.20	2.10
18	9.0	27000	0.40	0.00	0.10
19	9.5	28500	0.00	0.00	0.00
20	10.0	30000	2.50	2.50	1.20

Successive predominant velocities in *FS* are radial at, *2x* (v_H= 7.4 mm/s and v_V= 7.49 mm/s), *1x*(v_H= 6.62 mm/sand v_V= 6.23 mm/s) and *3x* (v_H= 5.6mm/s, v_V= 5.15 mm/s). This feature clearly indicates Parallel Misalignment.

5. FAULT DIAGNOSIS USING *ANFIS*

In the field of *AI*, neuro-fuzzy logics (*NFL*), refers to combinations of *ANN* and fuzzy logics. *NFL* was proposed by J. S. R. Jang [10]. It is hybridization of neuro and fuzzy results in an intelligent system that synergizes these two techniques by combining human-like reasoning style of fuzzy systems *(FL)* with learning and connectionist structure of neural networks (*NN*). Main strength of the *NFL* systems is that they are universal approximates with the ability to solicit interpretable *if-then* rules. The strength of *NFL* systems involves two contradictory requirements in fuzzy modeling, interpretability versus accuracy.

The objective of this research is to detect condition of air compressor, as to whether it is *Normal (0)* or *Fault (1)* at *MNDE*. Simulation and validation of a 3 inputs-1output Sugeno type *ANFIS* model considered for Condition monitoring is illustrated in Figure 6.

A data set consist of tuple of a (1, 3) vectored input data and a (1, 1) output vector. Behavior of mill stand was captured as vibration measurements, v_H, v_V and v_A, of a location at *MNDE*, from a triaxial accelerometer. The input data are extracted from the vibration features as maximum of the velocity measurements in each direction, v_{Hm}, v_{Vm} and v_{Am}.

The outputs are coded as *Normal-0* and *Fault-1,* and are assigned to the corresponding input vector in the data set. The output state is considered as *Normal-0*, if (v_{Hm}, v_{Vm} & v_{Am}) $\leq$ 4.5 mm/s and otherwise as *Fault-1*, if the (v_{Hm}, v_{Vm} or v_{Am})> 4.5 mm/s.

Each one of the input parameters v_{Hm}, v_{Vm} and v_{Am} was adjusted using two input *mf's* as *L* if there magnitude is ≤ 4.5 mm/s, else, as *H.* 200 datasets were used for the purpose. One new data set representing the two output states each was chosen for evaluation. A brief procedure followed using *MATLAB GUI* is as illustrated in Figure 6.

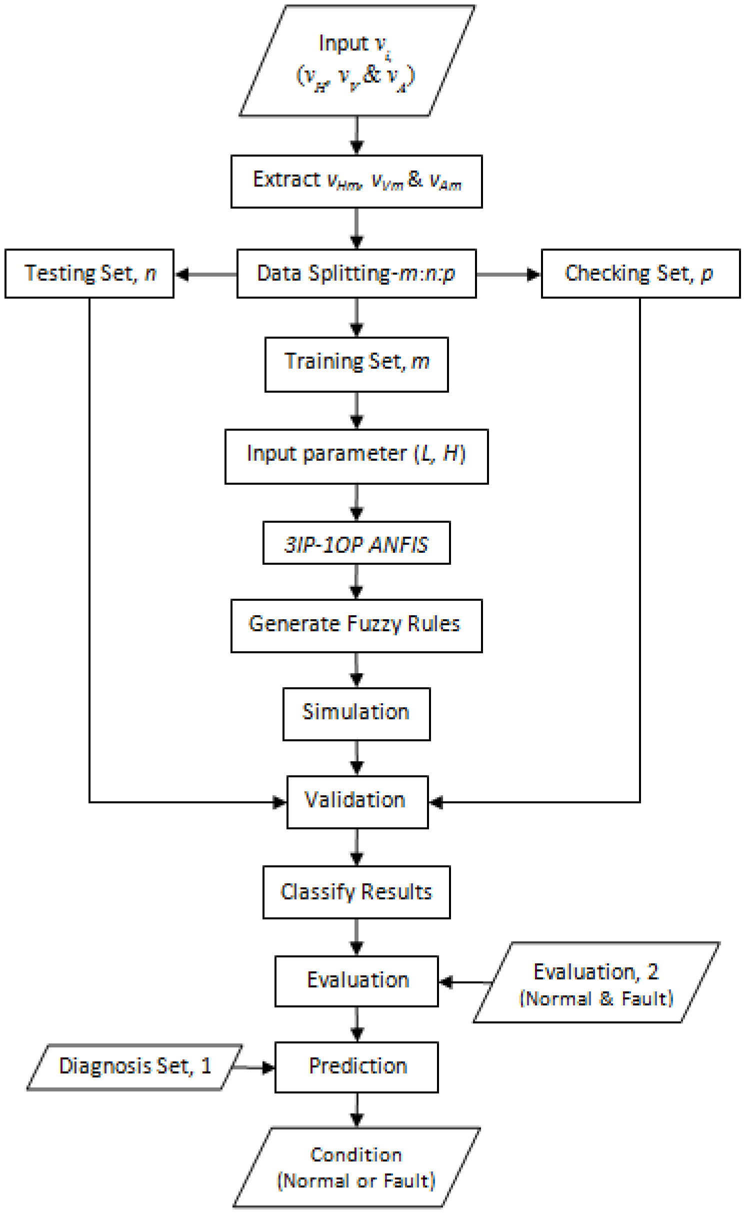


Figure 6: Condition Monitoring of Air Compressor (Condition-Normal (0) or Fault (1))

5.1 *ANFIS* Structure

Figure 7 gives the *ANFIS* Model Structure for Condition Monitoring of rotating machinery.

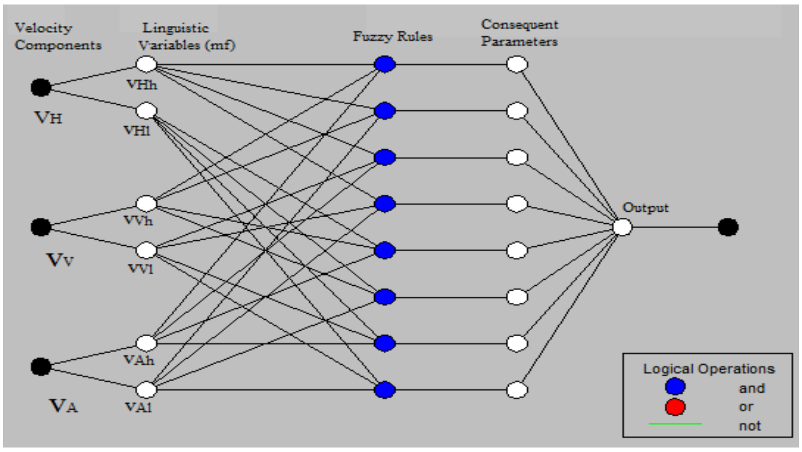


Figure 7: ANFIS Model Structure of Condition Monitoring

It consists of a Sugeno type 3 inputs (v_{Hm}, v_{Vm} & v_{Am}) and 1 output (i. e., Condition) structure. It has two input *mf*'s (*L, H*) and two outputs *mf's* (*Normal-0* and *Fault-1*). Information of *ANFIS* model is given in Table 4. The data set divided into 50:25:25 as Option-I and 60:20:20 as Option –II used for training, testing and checking respectively for s stable and accurate responses with a few exceptions.

Table 4: *ANFIS* Model Information

Sl. No.	Option	I	II
1	Number of nodes	34	
2	Number of linear parameters	32	
3	Number of nonlinear parameters	12	
4	Total number of parameters	44	
5	Number of training data pairs	98	120
6	Number of checking data pairs	0	
7	Number of fuzzy rules	8	

A difference between the two options is in training data can be noted. It consists of two input mf's (*L, H*) and two output mf's (i. e., *Normal*-0 and *Fault*-1).

Figure 8 shows the verbal rule set of the *ANFIS* Model. It shows a set 8 rules for the model describing various combinations of inputs for a specific total of two outputs, which describe the fuzzy logics of condition monitoring system.

1. If (vHm is H) and (vVm is H) and (vAm is L) then (condition is Fault) (1)
2. If (vHm is H) and (vVm is L) and (vAm is H) then (condition is Fault) (1)
3. If (vHm is H) and (vVm is L) and (vAm is L) then (condition is Fault) (1)
4. If (vHm is L) and (vVm is H) and (vAm is H) then (condition is Fault) (1)
5. If (vHm is L) and (vVm is H) and (vAm is L) then (condition is Fault) (1)
6. If (vHm is L) and (vVm is L) and (vAm is H) then (condition is Fault) (1)
7. If (vHm is H) and (vVm is L) and (vAm is L) then (condition is Fault) (1)
8. If (vHm is L) and (vVm is L) and (vAm is L) then (condition is Normal) (1)

Figure 8: Rule Set of the Condition Monitoring *ANFIS* Model

Eight rules that lead to the two distinct output states *0* and *1* are enumerated, along with the respective input combination with *AND* logic.

5.2 Training

Figure 9 shows the trend of training error, Root Mean Square Error (*RMSE*) as training progresses up to the steady

level.

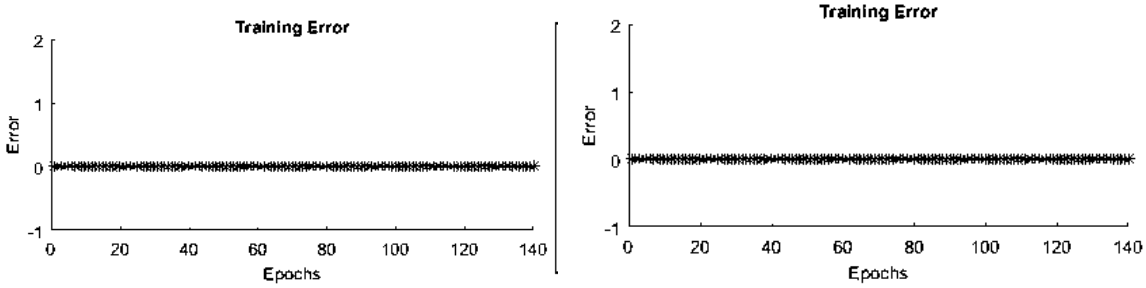


Figure 9: Trend of Training Errors

It can be seen that the epoch reaches 1, with a jump and it gradually reduces to an acceptable and remains steady then onwards. Zero error tolerance was used as criterion for stopping training. The training will stop after the training data error reaches the specified tolerance limits zero.

Significant error of training trends obtained from the command line output for both options, are shown in Table 5. The data set divided into 50:25:25 as option-I and 60:20:20 as Option –II used for training, testing and checking respectively for s stable and accurate responses with a few exceptions.

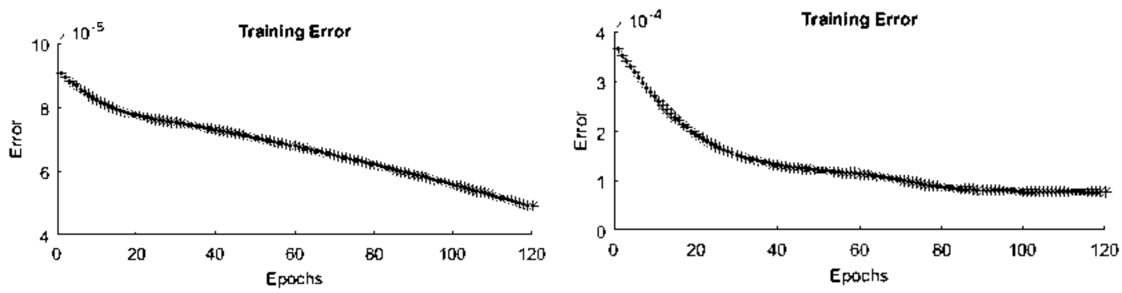
Table 5: Trend of Training Errors

Significant Epoch	Option I		Option II	
	Epoch	***RMSE***	**Epoch**	***RMSE***
Start	001	0.000939958	001	0.00279489
-	100	0.000114478	100	0.00066627
-	120	9.0692e-05	120	0.000364929
Steady	120	9.0692e-05	120	0.000364929
End	140	2.84496e-05	140	7.92324e-05

The epoch, at which the error levels off steadily is at 120 (120) and to a lowest possible *RMSE*, 2.84496e-05 (7.92324e-05) in Option I (Option II) scheme. The training can be stopped at 140 (140) for Option I (Option II). Further, it can be seen that the Option I has the least error and becomes stable early.

5.3 Testing

Figure 10 shows training errors during validation of model for given set of data measures the process capability. It can be observed that, a stable *RMSE* of 7.92324e-05 was minimal in Option I.

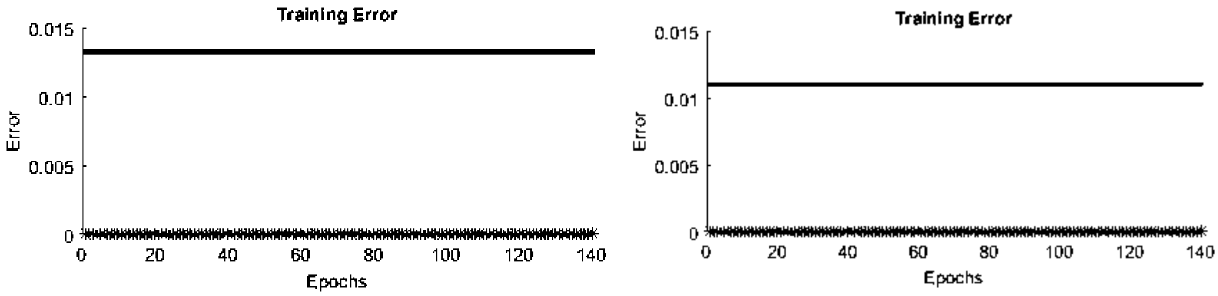


(a) Option I (7.92324e-05) **(b) Option II (4.86407e-05)**

Figure 10: Training Error vs Testing Data

5.4 Checking

Figure 11 shows training *RMSE*, *Te* and Checking *RMSE*, *Ce* while evaluation of the *ANFIS* model for given set of data.



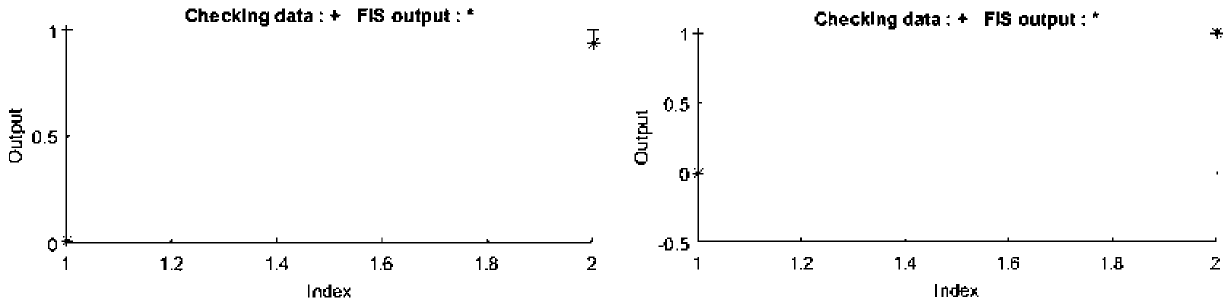
(a) Option I (*Te*=7.92324e-05, *Ce* = 0.0134414) **(b) Option II (*Te*=4.86407e-05, *Ce*= 0.0114286)**

Figure 11: Training Error & Checking Data

The structure of error level for training and checking data sets are steady and similar. This is a validation of the structural stability of the system. There was no over fitting in both the schemes as the training and checking error curves are linear and horizontal. Training and checking have become stable at *RMSE* of 7.92324e-05 (4.86407e-05), whereas, checking becomes stable at *RMSE* of 0.0134414 (0.0114286) in Option I (Option II).

5.5 Diagnosis

The diagnosis data fetched from vibration analysis using *FFT* was evaluated on the *ANFIS* to determine the actual current state of the Mill stand. Figure 12 shows the results of evaluation of diagnosis data set.



(a) Option I (RMSE =0.70275) **(b) Option II (RMSE=0.9994)**

Figure 12: Evaluation of Diagnostic Data Set

Notice that error between actual and predicted output is minimum in both options I (II) since *ARMSE* is 0.70275 (0.9994) is minimum in option I. It can be observed that, same output is predicted using *ANFIS*. This validates the *ANFIS* diagnosis and tallies very well with the results of vibration analysis.

5.6 Total Classification Accuracy (*TCA*)

MATLAB was used to compute total classification accuracy (*TCA*) for validating the response of *ANFIS* models. Option II, testing data of condition monitoring of Mill Stand at *MNDE*, was classified using *classify* function. Further a confusion matrix was obtained using *confusionmat*. Table 6 gives (2x2) confusion matrix showing the classification of results.

Table 6: Confusion Matrix of Air Compressor-MNDE

		AR	
	Output	*N*	*F*
PR	*N*	*3*	*0*
	F	*1*	*16*

AR –Actual Response, PR-Predicted Response; N-Normal, F-Fault

There are three criteria to determine the test performance of classifier. These criteria are Sensitivity (*ST*), Specificity (*SP*) and Total Classification Accuracy (*TCA*). Sensitivity can be obtained as, *ST=TP/AP*, where *TP* is the Number of True Positive Decisions and *AP* is the Number of Actual Positive Cases. i. e., *ST*=16/17=0.941 or 94.1%. Specificity can be obtained as, *SP=TN/AN*, where *TN* is the Number of True Negative Decisions and *AN* is the Number of Actually Negative Cases. i. e., *SP*=3/3=1 or 100%. Total Classification Accuracy can be obtained as, *TCA=TCD/TN*, where *TCD* is the Number of Correct Decisions and *TN* is the Total Number of Cases i. e., *TCA*=19/20=0.95 or 95%.

6. RESULTS AND DISCUSSIONS

Velocity components measured in v_H, v_V and v_A directions by tri axial accelerometer. They were processed through *FFT*. The successive predominant velocities, *1x* velocities v_H (= 5.2 mm/s) and v_V (= 5.2mm/s) are radial, hence the machine has Force Unbalance or Mechanical Looseness-A at *MNDE*. Velocity amplitudes predominant in succession, *1x* (v_A=7.2 mm/s), *2x* (v_A= 6.2 mm/s), and *3x* (v_A=5.2 mm/s), all in axial direction. It indicates Angular Misalignment in the machinery at *MDE*. Successive predominant velocities in *FS* are radial at, *2x* (v_H= 7.4 mm/s and v_V= 7.49 mm/s), *1x* (v_H= 6.62 mm/sand v_V= 6.23 mm/s) and *3x* (v_H= 5.6mm/s, v_V= 5.15 mm/s). This feature clearly indicates Parallel Misalignment at *FS*. This clearly indicates machinery fault condition and specific fault.

The *ANFIS* system was trained till the results obtained with minimum error levels off steadily is at 30(09) to a lowest possible Average Root Mean Square Error (*RMSE*), 2.84496e-05 (7.92324e-05) in Option I (Option II). The checking errors have become stable at an *RMSE* of 0.0134414 (0.0114286) in Option I (Option II). Testing *ARMSE* of 7.92324e-05 is found to be minimal in Option I. This validates the structural stability of the system and proves that the model perform correctly for any set of data obtained in the same way as that of training and checking. After training, two new data sets, one corresponding to each states *0* (Normal) and *1* (Fault) are loaded and evaluated. It can be observed that the predicted results are measured by the error between predicted values and actual values in the testing set both the classified and *ANFIS* results are same. Hence, *ANFIS* simulation is capable of predicting the vibration behavior of rotating machinery. Hence the evaluation is satisfactory.

Total Classification Accuracy can be obtained as, *TCA=TCD/TN*= 19/20 or 95%, where *TCD* is the Number of Correct Decisions and *TN* is the Total Number of Cases. Hence the performance of the *ANFIS* model is validated.

7. CONCLUSIONS

The main motivation for applying a Neuro-fuzzy computing approach is that, it combines the generalization capabilities of Neural Networks with the ease of interpretability and high expressive power of fuzzy rules in an effective way. Vibration signals were obtained from the Air Compressor using Tri-axial Accelerometer and *FFT*. These signals were processed in *MATLAB* using *ANFIS* tool for training, testing and checking to simulate the Air Compressor. The performance criterion of the *ANFIS* classifier was evaluated using confusion matrix. The total classification accuracy of

95% obtained proves the validation of the Air Compressor model. Neuro-Fuzzy Systems have high potential in diagnosis of machinery. The proposed ANFIS model has been found to be an effective tool for diagnosing faults.

8. ACKNOWLEDGEMENTS

We express sincere thanks to the management and staff of Jindal South West (*JSW*) Group, for providing access to the facility for conducting experiments on the machines of central maintenance department while in operation.

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